Tracing the Effects of Agricultural Commodity Prices and Food Costs

Catherine J. Morrison Paul and James M. MacDonald

We estimate a system of product and input-demand equations for food-processing industries to trace the links among farm commodity prices, food-processing costs, and food prices. Disembodied technical change, which likely reflects increasing consumer demand for convenience and product variety, has sharply reduced agricultural materials demand relative to most other food-processing inputs. This implies weakening impacts of farm price shocks on food prices. But improving quality and falling relative prices for agricultural inputs, in combination with increasing factor substitution, has counteracted these forces to encourage greater usage of agricultural inputs in food processing, and limit these trends.

Key words: agricultural inputs, costs, factor substitution, food prices, food processing.

Food prices today often appear less responsive to farm price shocks than in the past, a development sometimes attributed to failures in market institutions. However, powerful long-run technological and social changes, leading to adaptations in production processes and food consumption patterns, have also altered the demand for primary agricultural materials by changing the structure of food-processing industries. The social shifts surrounding the expanded role of women in the labor force represent one striking example of such changes. The fraction of married women in the labor force—less than one-third in 1960—rose sharply through the next three decades before stabilizing at around 61% in the 1990s. Such demographic shifts increased the demand for food products requiring less home preparation time, which, in combination with enhanced technology, has led to more in-plant processing of agricultural materials, and likely a growing share of nonagricultural inputs in food-processing costs.[1]

This inference is supported by Goodwin and Brester, who found an increased share of value-added, and a correspondingly reduced share for agricultural materials, in U.S. food-processing costs in the 1980s. A declining factor share should lead to a weaker linkage between farm prices and food prices. But other well-known factors also drive processors' production choices. The business environment, including market structure and the regulatory framework, has undergone important changes since the 1970s. Energy and labor prices have risen sharply compared to prices for agricultural commodities. Tax changes have had impacts on relative input prices by affecting the prices of capital inputs. Less well-documented technical changes, associated with capital equipment and the quality of agricultural materials, could also have had effects on the demand for agricultural products. These developments could also affect the linkages between farm and food prices.

In this study, we measure and evaluate these patterns for U.S. food-processing industries. We use a cost-function representation of input substitution resulting from technological shifts and price changes among capital, labor, energy, and three materials aggregates—agricultural, food, and "other" materials. This framework allows us to assess the roles of changes in food product demand, input prices, and food-processing technology on food processors' costs, input demands, and output prices, with a particular focus on the use of agricultural inputs. Our framework also facilitates consideration of technological factors affecting costs and

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[1] MacDonald et al. offer some examples of increased processing for meat products. Between 1982 and 1992, processors increased frozen ground beef patty production (typically sold to fast food chains) by 154%, and tripled output of already-cooked poultry products. Supermarket scanner data showed 197 distinct frozen dinner items containing meat in 1994; only 79 had been available in 1988. Similarly, 48 frozen breakfast items with meat ingredients were in distribution in 1994, and 49 frozen snack items, compared to 20 and 18, respectively, in 1988.

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factor demands, such as the quasi-fixed nature of capital, scale economies, technical change associated with either time trends (disembodied) or capital composition (embodied in capital), and agricultural innovations or market power embodied in input prices for agricultural commodities.

We find that the share of agricultural materials in processor costs fell during 1972–92, along with the sensitivity of food prices to farm prices. We also find that the direct effect of disembodied technical change in food processing has been agricultural materials-saving, likely induced by changes in product demand. But technological change eased substitution among factor inputs during the period, particularly in the 1980s, leading to a more price-elastic agricultural demand and lower relative farm prices, and muting the effects of direct technical change on agricultural demand. Moreover, we find that improved quality of agricultural materials meant that effective prices for those inputs fell even faster—relative to other input prices—than measured prices, inducing more substitution toward agricultural materials, and further limiting the effects of changes in consumption patterns.

The Model

Our framework assumes that food processors choose inputs to minimize costs, given input prices and output levels faced in supply- and demand-side markets. The cost model is specified in terms of true economic or "effective" prices, to recognize that effective prices for some inputs may not be equivalent to their measured counterparts, due to imperfect markets or measurement associated with quasi-fixities, deviations from perfect competition, or innovation and quality changes. The resulting cost model is also augmented to characterize profit-maximizing output prices and quantities, through an equality of the associated marginal cost and marginal revenue.

More formally, the technology and cost-minimizing behavior underlying the observed production structure can be represented by a total cost specification of the form $\mathrm{TC} = \mathrm{TC}(Y, \mathbf{p}, \mathbf{r})$, where Y is (food) output, $\mathbf{p}$ is a vector of variable input prices, and $\mathbf{r}$ is a vector of exogenous technological determinants. The TC–Y relationship, summarized by the elasticity of total cost with respect to output, $\varepsilon_{\mathrm{TC,Y}} = \partial \ln \mathrm{TC}/\partial \ln Y$, represents the shape of the minimized long-run cost curve, given observed factor prices and the existing technological base. Changes in components of the $\mathbf{p}$ and $\mathbf{r}$ vectors affect this cost relationship, and thus implied overall costs and input demands. Measures of these cost structure patterns may thus be derived in terms of first and second-order elasticities with respect to these arguments of the cost function.

Internal or external adjustment costs may, however, sever the equivalence of the observed price of input x_k, p_k, and its true economic return or shadow value, p_k^*, and thus the duality underlying the cost function. In this case, observed costs exceed minimum possible long-run production costs. Other discrepancies between the observed and effective or shadow price, observationally equivalent to adjustment costs, may stem from other input market imperfections such as imperfect competition in factor markets, or unmarketed (or unmeasured) characteristics.

One way to deal with such implicit costs is to include x_k instead of p_k as an argument in the (variable) cost function, and thus represent the shadow value wedge as $\partial \mathrm{TC}/\partial x_k = p_k - p_k^* \neq 0$.[2] Alternatively, the true economic, shadow, or effective price of input x_k, $p_k^* = p_k + \lambda_k$, may be directly incorporated into the cost function, where λ_k represents the wedge between p_k and p_k^*. This approach is particularly appealing if the cross- or interaction-terms from a model incorporating x_k as an argument seem uninformative, but an imperfect market gap, λ_k, seems to exist (λ_k statistically deviates from zero).[3] If instead p_k^* appears well approximated by p_k, or $\lambda_k \approx 0$, one can assume that rigidities or other input market imperfections are not binding constraints on, or determinants of, measured cost structure patterns.

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[2] This requires defining $\mathrm{TC}(\cdot) = \mathrm{VC}(Y,\mathbf{p},\mathbf{r},x_k) + p_k x_k$ and $p_k^* = -\partial \mathrm{VC}/\partial x_k$, where VC is variable costs, $p_k^* = p_k$ in full long-run equilibrium (and p_k^* is often instead denoted Z_k). See Morrison for elaboration of a more detailed representation of quasi-fixity, including a dynamic structure explicitly capturing adjustment costs. Others, including Paul (2000, 2001) and Bernstein (1992, 1994), also specify fuller models of market structure and its impact on the wedge between actual and shadow or effective price, following Lau. The driving forces for such a wedge—fixities and market structure—as well as the possibility of measurement error, are proxied in our specification by a simple hedonic model allowing for deviations in the levels and trends of effective as compared to observed prices of M_O, K, and Y. As noted by an anonymous referee, our approach may simply make the function more flexible. But that is also true of more explicit structural models of the form of the wedge between p_k^* and p_k.

[3] That is, incorporating x_k directly into the cost function allows the deviation of the shadow and market price, $p_k^* - p_k$, to depend on all arguments of the function if the cost function has a sufficiently flexible functional form. However, the cross-terms in this case were insignificant in preliminary empirical investigation, so this more complex model was not supported.

For our application, after preliminary investigation of estimation patterns, we adopted an effective price framework as that most consistent with our data. The total cost function for producing output in the U.S. food-processing sector then becomes $\mathrm{TC} = \mathrm{TC}(Y, \mathbf{p_v}, \mathbf{p_x^*}, \mathbf{r})$, where $\mathbf{p_v}$ represents the vector of observed variable input prices for factors that satisfy standard requirements for Shephard's lemma to be valid, and $\mathbf{p_x^*}$ is a vector of effective prices that deviate from observed prices by the additive factors $\lambda_{\mathbf{x}}$.[4] We found evidence of deviations between observed and effective or shadow prices for capital (K) and agricultural materials (M_{O}), but support for an assumption of no such deviations for labor (L), energy (E), and two materials inputs (food, M_{F}; and other, M_{O}), with prices p_{L}, p_{E}, p_{MF}, and p_{MO}. Demand decisions for these inputs are accordingly represented by $v_j = \partial\mathrm{TC}/\partial p_j$.

The effective price of capital may be defined as $p_{\mathrm{K}}^* = p_{\mathrm{K}} + \lambda_{\mathrm{K}}$, with the wedge λ_k potentially attributable to capital rigidities (adjustment costs) or unmeasured taxation or quality impacts. We tested various forms for λ_{K} to establish their empirical justification in terms of significance of the parameters, robustness of the overall results, and plausibility of resulting elasticities. The specification chosen is an augmented version of an additive shift factor embodying technical change trends; $\lambda_{\mathrm{K}} = \lambda_{\mathrm{K1}} + \lambda_{\mathrm{Kt}}t + \lambda_{\mathrm{K2}}t2$, where t is a trend term and $t2$ a dummy variable reflecting post-1980 structural change. This is essentially a simple hedonic model recognizing differences in the level and trend of quality-adjusted prices not fully captured in measured p_{K}, which might be expected to arise from internal or external adjustment costs.

Similarly, we defined the effective agricultural materials price as $p_{\mathrm{MA}}^* = p_{\mathrm{MA}} + \lambda_{\mathrm{MA}}$, with $\lambda_{\mathrm{MA}} = \lambda_{\mathrm{MA1}} + \lambda_{\mathrm{MAt}}t + \lambda_{\mathrm{MA2}}t2$. The existence of such a gap between p_{MA} and p_{MA}^* is plausible on several grounds. For example, if the processing industries perceive some market power over agricultural prices, the (higher) marginal price, not the observed average price, will drive agricultural input demand ($\lambda_{\mathrm{MA}} > 0$). Alternatively, or in combination, technical change embodied in higher quality agricultural products could imply lower effective prices of agricultural materials compared to their measured values ($\lambda_{\mathrm{MA}} < 0$). With p_{MA}^* as an argument in the cost function, the sign and thus interpretation of λ_{MA} may be established empirically.[5]

The variables in the **r** vector, reflecting the industry's technological base, include a time trend t representing disembodied technical change, and an intercept dummy shift $t2$ capturing structural shifts in the 1980s as compared to the 1970s ($t2 = 1$ for 1982, 1987, and 1992). A capital equipment to structures ratio, (EQ/ST = ES), is also used to represent technology embodied in the capital stock. The resulting model allows both for technical change embodied in K and M_{A}, through the inclusion of t and $t2$ in the effective price specification, and for disembodied technical change, through the time terms in the **r** vector.

Our model accommodates output supply and pricing decisions by also permitting output price to differ from marginal cost. This extension of the cost function framework imposes a standard profit-maximizing condition underlying output choice (equality of marginal cost, MC, and marginal revenue, MR), implicitly assuming that downward-sloping firm demand curves drive any measured gaps between output price and marginal revenue. This is implemented through the optimization equation $\mathrm{MR} = p_{\mathrm{Y}} + \partial p_{\mathrm{Y}}/\partial Y \times Y = \partial\mathrm{TC}/\partial Y = \mathrm{MC}$, so $\partial p_{\mathrm{Y}}/\partial Y \times Y$ reflects the wedge between MR and MC. We found $\partial p_{\mathrm{Y}}/\partial Y$ to be well approximated by a parameter, λ_{Y}, which is consistent with a linear demand curve. So the effective output price is $p_{\mathrm{Y}}^* = p_{\mathrm{Y}} + \lambda_{\mathrm{Y}}Y$, and the resulting optimization equation becomes $p_{\mathrm{Y}}^* = \mathrm{MC}$, or $p_{\mathrm{Y}} = -\lambda_{\mathrm{Y}}Y + \mathrm{MC}$. Alternative treatments tried, with λ_{Y} specified as a function of other exogenous variables, including t and $t2$, caused no substantive impact on the resulting estimated patterns.[6]

Based on the resulting model, consisting of the total cost function $\mathrm{TC} = \mathrm{TC}(p_{\mathrm{MA}}^*, p_{\mathrm{K}}^*, p_{\mathrm{L}},$

[4] See Fulginiti and Perrin for a motivation and development of a similar approach.

[5] As pointed out by an anonymous referee, such mechanisms may imply that p_{MA}^* (or p_{K}^*) is endogenous. That is, if λ_{MA} or λ_{K} differ from zero due to external adjustment costs or imperfect competition, for example, the implied upward sloping supply curve should be represented to fully capture all market structure impacts on behavior. A similar argument may be made for output. However, appropriately characterizing such input supply and output demand relationships, especially for our broad range of industries, is not very feasible, so if attempted specification errors will be embedded in the full estimated model. In addition, a variety of different forces may underlie these price deviations, rather than just market structure.

[6] λ_{Y} represents the slope of the output-demand function, so only arguments with second-order effects (impacts on the slope as well as just a shift impact) would appear in $\lambda_{\mathrm{Y}}(\cdot)$. Fixed effects reflecting industry-specific differences were also incorporated for estimation of p_{Y}^*.

$p_{\mathrm{MF}}, p_{\mathrm{E}}, p_{\mathrm{MO}}, Y, \mathrm{ES}, t, t2)$ and associated input-demand and output-supply (pricing) optimization equations, we can quantify and evaluate a variety of issues raised above. In particular, we can assess the impact of agricultural prices on food prices, and identify the means by which the relationship changed through time. We can also determine the paths by which various factors drove processing costs during the time period under consideration.

To accomplish these tasks we decompose observed temporal total cost changes $\mathrm{dTC}/\mathrm{d}t$ into its driving forces, by quantifying the total derivative written in terms of elasticities as

$$(1)\qquad \mathrm{d}\ln\mathrm{TC}/\mathrm{d}t = \Sigma_i \varepsilon_{\mathrm{TC,pi}}\, \mathrm{d}\ln p_i/\mathrm{d}t + \varepsilon_{\mathrm{TC,Y}}\, \mathrm{d}\ln Y/\mathrm{d}t + \varepsilon_{\mathrm{TC,ES}}\, \mathrm{d}\ln\mathrm{ES}/\mathrm{d}t + \varepsilon_{\mathrm{TC},t2}\, \mathrm{d}t2/\mathrm{d}t + \varepsilon_{\mathrm{TC}}, t$$

where $\varepsilon_{\mathrm{TC,pi}}$ are estimated cost elasticities with respect to the various input prices, $\partial\ln\mathrm{TC}/\partial\ln p_i$, and the other (analogously defined) elasticities, denoted by ε, capture responses to changes in output and technological factors.[7] All the elasticities can be derived using the estimated parameters of our model. The associated time derivatives such as $\mathrm{d}\ln p_i/\mathrm{d}t$ simply reflect changes in the data between the previous and current time period (t).

By defining the individual terms of (1) as "contributions" (C), we can rewrite (1) as

$$(2)\qquad \mathrm{d}\ln\mathrm{TC}/\mathrm{d}t = \Sigma_i C_{\mathrm{TC,pi}} + C_{\mathrm{TC,Y}} + C_{\mathrm{TC,ES}} + C_{\mathrm{TC},t2} + C_{\mathrm{TC},t}$$

where the $C_{\mathrm{TC}}, \cdot$ measures capture the responsiveness (elasticity), weighted by the actual rate of change in the exogenous variable. The variable $t2$ appears even though it is a dummy variable, although its impact is only reflected in the time period the dummy variable becomes one.[8]

Each term underlying (2) has a specific interpretation as a cost driver. For example, the scale elasticity $\varepsilon_{\mathrm{TC,Y}}$ captures the extent of scale economies. The contribution of such economies to observed cost changes, $C_{\mathrm{TC,Y}}$, depends on both the elasticity, $\varepsilon_{\mathrm{TC,Y}}$, and the actual output (scale of production) change, $\mathrm{d}\ln Y/\mathrm{d}t$. Similarly, the cost-contribution of an input-price change depends both on the cost elasticity with respect to the price, and on the actual price change.

The other contributions represent shifts in the cost function from external technological and economic forces. Cost impacts of observed adaptations toward enhanced capital equipment, or embodied technical change, are measured by $C_{\mathrm{TC,ES}}$, and $C_{\mathrm{TC},t}$ ($\varepsilon_{\mathrm{TC},t}$) is typically interpreted as disembodied technical change that results in a downward shift of the cost relationship over time, while $C_{\mathrm{TC},t2}$ captures a structural shift in the 1980s, as suggested by Goodwin and Brester.

Finally, given the forms for p^*_{K} and p^*_{MA}, we can distinguish the direct (dir) and indirect (ind) cost impacts of technical changes, where the indirect impact works through the effects of t (or, analogously, $t2$) on λ_{K} and λ_{MA}. For example, the implied total (tot) t impact is

$$(3)\qquad \begin{aligned} \varepsilon_{\mathrm{TC},t\,(\mathrm{tot})} &= \partial\ln\mathrm{TC}/\partial t + \partial\ln\mathrm{TC}/\partial\ln p^*_{\mathrm{MA}}\partial\ln p^*_{\mathrm{MA}}/\partial t + \partial\ln\mathrm{TC}/\partial\ln p^*_{\mathrm{K}}\partial\ln p^*_{\mathrm{K}}/\partial t \\ &= \varepsilon_{\mathrm{TC},t\,(\mathrm{dir})} + \varepsilon_{\mathrm{TC,pMA}}\,\varepsilon_{\mathrm{p^*MA},t} + \varepsilon_{\mathrm{TC,pK}}\,\varepsilon_{\mathrm{p^*K},t} \\ &= C_{\mathrm{TC},t\,(\mathrm{dir})} + C_{\mathrm{TC,p^*MA},t} + C_{\mathrm{TC},p^*\mathrm{K},t}. \end{aligned}$$

In addition to cost effects, we are interested in the specification and evaluation of agricultural materials demand. The cost function model by definition represents a system of input-demand equations (by Shephard's lemma, applied to the effective prices), so $M_{\mathrm{A}} = \partial\mathrm{TC}/\partial p^*_{\mathrm{MA}}$. When $\mathrm{TC}(\cdot)$ is approximated by a flexible form that recognizes all second-order relationships, this agricultural materials demand equation depends on all cost function arguments. Thus, the driving forces for observed changes in agricultural materials (M_{A}) demand can be decomposed, similarly to those for $\mathrm{TC}(\cdot)$, as

$$(4)\qquad \mathrm{d}\ln M_{\mathrm{A}}/\mathrm{d}t = \Sigma_i \varepsilon_{\mathrm{MA,pi}}\, \mathrm{d}\ln p_i/\mathrm{d}t + \varepsilon_{\mathrm{MA,Y}}\, \mathrm{d}\ln Y/\mathrm{d}t + \varepsilon_{\mathrm{MA,ES}}\, \mathrm{d}\ln\mathrm{ES}/\mathrm{d}t$$

[7] The $\varepsilon_{\mathrm{TC},p*k}$ elasticities are weighted by the observed changes in p_k, since (as elaborated later) we have expanded our interpretation of the t effect to include the indirect effect via the $\mathrm{d}p^*_k/\mathrm{d}t$ trend, so this impact is double-counted if it also appears multiplicatively with $\varepsilon_{\mathrm{TC},p*k}$.

[8] For our analysis, therefore, the impact is captured for 1977–82 since $t2 = 1$ for the 1982, 1987, and 1992 time periods. Also, since the time dimension of our data is over five-year intervals, to turn these changes into annual averages the estimated measures are divided by five.

$$+\varepsilon_{\mathrm{MA},t2}\,\mathrm{d}t2/\mathrm{d}t+\varepsilon_{\mathrm{MA},t}$$
$$=\Sigma_i C_{\mathrm{MA,pi}}+C_{\mathrm{MA,Y}}+C_{\mathrm{MA,ES}}$$
$$+C_{\mathrm{MA},t2}+C_{\mathrm{MA},t}.$$

The elasticities in (4), such as $\varepsilon_{\mathrm{MA,pi}} = \partial\ln M_{\mathrm{A}}/\partial\ln p_i$, quantify the shape of and shifts in the M_{A} demand curve for changes in p_{MA} and other arguments of the function, and the contribution measures, C_{MA}, reflect the actual contributions given observed changes in these determinants. In particular, $\varepsilon_{\mathrm{MA,pi}}$ indicates the responsiveness of agricultural demand to its own price for $i = M_{\mathrm{A}}$, and substitutability between input v_{i} and M_{A} for other inputs. Similarly, the M_{A}-specific impacts of changes in the scale of production or technological factors are captured by the analogously defined $\varepsilon_{\mathrm{MA,Y}}$ and $\varepsilon_{\mathrm{MA,rn}}$ elasticities.

For example, if $\varepsilon_{\mathrm{MA,Y}} > 1$ product demand expansions imply disproportionate increases in agricultural product demand, and scale increases are M_{A}-using. If $\varepsilon_{\mathrm{MA,Y}} > \varepsilon_{\mathrm{TC,Y}}$ expansions are also relatively M_{A}-using, or biased. If $\varepsilon_{\mathrm{MA},rn} < 0$ for $r_n = t2$, the demand for agricultural commodities was more limited, given other economic and technological factors, in the 1980s than in the 1970s. This suggests a structural shift toward lower M_{A}-intensity of production (possibly induced by output demand composition changes). $\varepsilon_{\mathrm{MA},t}$ indicates the force of disembodied technical change, or trend, on M_{A} demand. And if $\varepsilon_{\mathrm{MA},t}$ deviates from the overall cost change $\varepsilon_{\mathrm{TC},t}$, this is often referred to as a technical change bias.

The total t- or $t2$-effect on M_{A} demand can also be divided into its direct and indirect (through p_k^*) impacts, as in (3), which for t becomes

$$(5)\qquad \varepsilon_{\mathrm{MA},t\,(\mathrm{tot})}=\varepsilon_{\mathrm{MA},t\,(\mathrm{dir})}+\varepsilon_{\mathrm{MA,pMA}}\,\varepsilon_{\mathrm{p^*MA},t}+\varepsilon_{\mathrm{MA,pK}}\,\varepsilon_{\mathrm{p^*K},t}$$
$$\text{or } C_{\mathrm{MA},t\,(\mathrm{tot})}=C_{\mathrm{MA},t\,(\mathrm{dir})}+C_{\mathrm{MA,p^*MA},t}+C_{\mathrm{MA,p^*K},t}.$$

The individual components of (5) allow us to source the effects of technical change on agricultural materials demand. Such measured input-demand patterns in turn provide implications about the prices that agricultural producers will receive for their products.

The definition of the marginal cost of output, $\mathrm{MC} = \partial\mathrm{TC}/\partial Y$, provides a final set of second-order relationships with useful insights. For a flexible cost function, the MC relationship will depend on all arguments of the total cost function, so we can decompose it as

$$(6)\quad \mathrm{d}\ln\mathrm{MC}/\mathrm{d}t=\Sigma_i\varepsilon_{\mathrm{MC,pi}}\,\mathrm{d}\ln p_i/\mathrm{d}t+\varepsilon_{\mathrm{MC,Y}}\,\mathrm{d}\ln Y/\mathrm{d}t+\varepsilon_{\mathrm{MC,ES}}\,\mathrm{d}\ln\mathrm{ES}/\mathrm{d}t+\varepsilon_{\mathrm{MC},t}$$
$$=\Sigma_i C_{\mathrm{MC,pi}}+C_{\mathrm{MC,Y}}+C_{\mathrm{MC,ES}}+C_{\mathrm{MC},t}$$

where, for example, $\varepsilon_{\mathrm{MC,pi}} = \partial\ln\mathrm{MC}/\partial\ln p_{\mathrm{i}}$. This decomposition allows consideration of two issues of interest, the differential impacts of economic and technological changes on returns to scale, and on the extent of market power, in the food industries.

In particular, we can consider how p_{MA} changes affect marginal as compared to average cost, and thus $\varepsilon_{\mathrm{TC,Y}} = \mathrm{MC}/\mathrm{AC}$, using the $\varepsilon_{\mathrm{MC,pMA}}$ and $\varepsilon_{\mathrm{TC,pMA}}$ elasticities. Also, based on our output-pricing expression $p_{\mathrm{Y}} = -\lambda_{\mathrm{Y}}Y + \mathrm{MC}$, we can construct a decomposition of p_{Y} analogous to those presented above, with the difference from that for $\mathrm{MC} = p_{\mathrm{Y}}^*$ depending on λ_{Y}. This may be used to evaluate how p_{MA} changes impact p_{Y} as compared to MC, which provides some information on the pass-through of agricultural materials prices to food prices, and on the implications for markup behavior ($p_{\mathrm{Y}}/\mathrm{MC}$).

The Data

For the empirical implementation of our model, we required data on prices and quantities of output and inputs for industries in the U.S. food-processing sector. Our base data were taken from the four-digit manufacturing NBER (National Bureau of Economic Research) productivity database, which is often used as a foundation for production structure studies, such as Griliches and Lichtenberg; Bartlesman, Caballero, and Lyons; and Fixler and Siegel.

We also, however, needed to distinguish cost shares for three materials aggregates—agricultural materials, food materials (shipped among food-processing establishments), and other materials. We used Census of Manufactures data to calculate the share of each materials aggregate in the industry value of shipments for which cost information is available, and adjusted the published data in two ways.[9] First, we subtracted re-sales (purchased materials that are not processed before being resold, which are important in some industries) from the value of shipments, to better capture manufacturing output. Second, some small establishments do not separately report individual materials purchases, but instead report all materials in an "n.s.k." (not separately classified) category. We allocated n.s.k. shipments to agricultural, food, and other materials categories in proportions equivalent to those reported by the larger institutions.

Materials input-price series were constructed primarily from commodity producer price indexes (PPIs) from the Bureau of Labor Statistics. In cases where an industry consumed several specific agricultural or food materials, an aggregated materials price index was constructed from the constituent materials indexes, with each price index weighted by its expenditure share in the Census aggregate. In the few cases where PPI indexes were not available, we constructed indexes from average price series maintained by USDA's National Agricultural Statistics Service. The resulting data panel covers five-year intervals from 1972 through 1992, for 34 consistently defined four-digit SIC industries in the U.S. food-processing sector (SIC 20).

Empirical Implementation

Estimation of our model also required more explicit specification of the cost function and the resulting system of estimating equations. We used a version of the generalized Leontief (GL) cost function, called a GL-quadratic (GL-Q) by Paul (2000), which takes the form

$$
\begin{aligned}
(7)\quad \mathrm{TC}(Y,\mathbf{p},\mathbf{r}) = {} & \Sigma_j \Sigma_I \delta_{jI}\, \mathrm{p}_j\, \mathrm{DUM}_{\mathrm{I3}} \\
& + \Sigma_j \Sigma_I\, \delta_{j\mathrm{YI}} p_j \mathrm{DUM}_{\mathrm{I4}} Y \\
& + \Sigma_k \Sigma_I \delta_{kI} p_k^*\, \mathrm{DUM}_{\mathrm{I3}} \\
& + \Sigma_k \Sigma_I \delta_{k\mathrm{YI}} p_k^*\, \mathrm{DUM}_{\mathrm{I4}} Y + \Sigma_{\mathrm{j}} \Sigma_i \alpha_{ji} p_j^{.5} p_i^{.5} \\
& + \Sigma_j \Sigma_k \alpha_{jk} p_j^{.5} p_k^{*.5} + \Sigma_k \Sigma_l \alpha_{kl} p_k^{.5} p_l^{.5} \\
& + \Sigma_k \delta_{kY} p_{k\mathrm{Y}}^* + \Sigma_k \Sigma_n \delta_{\mathrm{kn}} p_k^*\, r_n \\
& + \Sigma_k p_k^* \big(\gamma_{\mathrm{YY}} Y^2 + \Sigma_n \gamma_{\mathrm{Y}n} r_n Y \\
& + \Sigma_m \Sigma_n \gamma_{mn} r_m r_n\big) + \Sigma_j \delta_{j\mathrm{Y}} p_j Y \\
& + \Sigma_j \Sigma_n \delta_{jn} p_j r_n + \Sigma_j p_j \big(\gamma_{\mathrm{YY}} Y^2 \\
& + \Sigma_n \gamma_{\mathrm{Yn}} r_n Y + \Sigma_m \Sigma_n \gamma_{mn} r_m r_n\big)
\end{aligned}
$$

where I denotes industry, and $\mathrm{DUM}_{\mathrm{I3}}$, $\mathrm{DUM}_{\mathrm{I4}}$ represent three- and four-digit industry dummy variables. The model thus pools the industry data, but includes fixed industry effects, incorporated in such a manner that linear homogeneity in input prices is maintained.[10] For example, the first term in (7) represents a sum across input price and industry dummies, so that each input equation includes industry fixed effects. Also, although input prices are conditioned on three-digit industry dummies, output is conditioned on four-digit dummies, because the greater industry detail provided by four-digit fixed effects was not significant for the input-demand equations, but was for the output-pricing equation and cross price-output industry effects.[11]

The final estimating model is comprised of a system of demand equations for the inputs (L, K, E, M_{A}, M_{F}, M_{O}), and a pricing equation for output. As alluded to above, the input-demand equations are constructed according to Shephard's lemma; $v_{\mathrm{j}}(\cdot) = \partial\mathrm{TC}(\cdot)/\partial p_j$ ($j = L$, E, M_{F}, M_{O}) and $x_k(\cdot) = \partial\mathrm{TC}(\cdot)/\partial p_k^*$ ($k = M_{\mathrm{A}}$, K), where $p_k^* = p_k + \lambda_k$, and $\lambda_k = \lambda_{k1} + \lambda_{kt}t + \lambda_{\mathrm{k}2}t2$. Also, for the output-pricing equation $p_{\mathrm{Y}} = -\lambda_{\mathrm{Y}} Y + \partial\mathrm{TC}/\partial Y$, derived from equating MR and MC, λ_{Y} was differentiated across industries to incorporate fixed effects into this relationship; $\lambda_{\mathrm{Y}} = \Sigma_{\mathrm{I}}\lambda_{\mathrm{YI}} D_{\mathrm{I4}}$.

Estimation was carried out by seemingly unrelated (SUR) regression, with the potential for heteroskedasticity accommodated by techniques in TSP that allow standard errors to be computed from a heteroskedastic-consistent

[9] Establishments are required to report consumption of major materials that are important components of production costs, where important is defined as expenditures exceeding a particular value—usually \$10,000.

[10] As pointed out by an anonymous referee, pooling the data in this manner may not be fully justifiable due to heterogeneity across industries (although it seems clearly preferable to aggregation across the industries). In preliminary empirical investigation, however, we found both that additional fixed effects were insignificant for the input demand equations, and that adding more interaction terms to allow further distinction between industries did not tend to change the results substantively, yet increased overall insignificance. We also could not incorporate a full range of such interaction terms, or estimate the industries separately, due to lack of df. Since including interaction terms would thus be of limited usefulness, we chose to remain with the simpler and more robust fixed effects specification.

[11] For example, dairy products is a three-digit industry class, which consists of four-digit industries such as fluid milk processing, cheese manufacturing, butter manufacturing, or ice cream, and frozen desserts. The inclusion of fixed effects means that our other coefficients, and the elasticity measures, should be interpreted as "within" estimates; they are relative to industry-specific means and thus reflect intra-industry variation.

matrix (Robust–White). An alternative approach to heteroskedasticity adjustment—to reconstruct the equations as input/output instead of input demand equations—was also tried in empirical estimation, but did not improve the estimates.

Although instrumental variables (IV) procedures such as three-stage least squares are often used in the literature on which this study is based, to accommodate potential endogeneity or measurement errors in the data, we did not rely on them for a variety of reasons. First, IV techniques frequently require an arbitrary specification of instruments, which can be problematic. In addition, models of this form are typically estimated with time series data, and often use lagged values of the observed arguments of the function as instruments. But this is not conceptually or empirically appealing for our application due to the short time series, as well as the five-year gaps between data points. Preliminary investigation was carried out to determine the sensitivity of the results to some IV specifications, but the results from these specifications were individually more volatile (less robust) and not as plausible as those from a basic SUR model. Because on balance the emerging story from the results was consistent with SUR estimates, we thus relied on SUR techniques for the final estimation.

Results

Appendix table A.1 displays the estimated parameters for our model (dummy terms are not included in the table since there are too many to be illuminating, but they are primarily statistically significant). The overall explanatory power of the model is indicated by the high R^2's for the estimating equations provided in appendix table A.2, including the total cost equation, which was not estimated but was fitted to determine the implied R^2. Many parameter estimates that are not individually statistically significant are jointly significant, such as the ES parameters mentioned above.[12] And the story emerging from the final model was robust to a variety of alternative specifications tried to evaluate sensitivity.[13]

Table 1. Total Cost Elasticities and Contributions

	$\ln\Delta$	$\varepsilon_{TC,i}$	$C_{TC,i}$
Input prices			
Agricultural materials	0.0547	0.2497*	0.0137
Food materials	0.0403	0.1031*	0.0042
Other materials	0.0653	0.1293*	0.0084
Labor	0.0908	0.0836*	0.0076
Capital	0.0680	0.4213*	0.0287
Energy	0.1186	0.0130*	0.0015
Output	0.0218	0.8677*	0.0191
Technical change			
Equipment and structures	0.0200	−0.0176	−0.0008
t		−0.0354*	0.0004
*t*2		0.0187*	−0.0141
Sum			0.0824

Note: The first column ($\ln\Delta$) capture annual average log differences, or growth rates, in the explanatory variables. Contributions (C) are elasticities times growth. All estimates are derived from parameters reported in appendix table 2. Asterisks denote 95% statistical significance.

Parameter estimates were used to construct the elasticity and contribution measures overviewed above, which were averaged across the whole sample, and separately for 1972–82 and 1982–92, to distinguish temporal patterns. The elasticity estimates were constructed by computing the indicators for each data point and then averaging across the sample under consideration. Statistical significance of these measures (since they involve combinations of parameters) was imputed by evaluating the elasticity estimates for the averaged data; values significantly different from zero at the 5% level are indicated by an asterisk.[14] In most cases, the significance implications were not data-dependent, although for some estimates the data point at which the measure was evaluated contributed to evidence of significance.

Total Cost Drivers

Consider first the elasticity and contribution measures presented in table 1 for total costs. The cost elasticity most directly associated with agricultural materials use, $\varepsilon_{TC,pMA}$, reflects the cost share of agricultural materials. The estimated average value, 0.25, indicates that rising p_{MA} has a substantive positive impact on

[12] One significance issue worth specific mention is that neither the λ_{MA1} or λ_{MA2} estimate in the final specification reach statistical significance at the 5% level. This was primarily due to insignificance of the level shift factor, λ_{MA1}, since if this is set to zero λ_{MA2} is significant. However, the measured elasticities varied negligibly with this adaptation, so to retain symmetry of the virtual price treatments we retained both parameters in the specification.

[13] We tried various alternative IV treatments, although as suggested in the text the specification of instruments for these treatments is arbitrary, and the results varied depending on the choice of instruments. Since the SUR estimates were less volatile, less arbitrary, and represented overall patterns effectively, these estimates were chosen for our final specification.

[14] We used the ANALYZ command in PC-TSP to construct these estimates, which required evaluating the significance for a single data point. We alternatively constructed *t*-statistics for the elasticities for individual observations and for averaged data.

Table 2. Temporal Total Cost Decompositions

	$\ln\Delta$	$\varepsilon_{TC,i}$	$C_{TC,i}$	$\ln\Delta$	$\varepsilon_{TC,i}$	$C_{TC,i}$>
	1972–82			1982–92		
Input prices						
Agricultural materials	0.1021	0.2734*	0.0279	0.0080	0.2263*	0.0018
Food materials	0.0687	0.1096*	0.0075	0.0123	0.0967*	0.0012
Other materials	0.1048	0.1382*	0.0145	0.0264	0.1206*	0.0032
Labor	0.1334	0.0951*	0.0127	0.0489	0.0723*	0.0035
Capital	0.1076	0.3715*	0.0400	0.0291	0.4703*	0.0137
Energy	0.2410	0.0122*	0.0030	−0.0019	0.0138*	0.0000
Output	0.0266	0.8677*	0.0191	0.0170	0.8871*	0.0150
Technical change						
Equipment and structures	0.0244	−0.0189	−0.0238	0.0156	−0.0592	−0.0009
t		0.0020*	0.0004		0.0388*	0.0077
*t*2		−0.2530*	−0.0123		−0.5203*	0.0000
Sum			0.0890			0.0417

Note: See table 1.

production costs, and thus strongly affects food-processing output and price. Note, however, that the overall contribution of agricultural prices to total cost increases, 1.4% per year over 1972–92, is much smaller than that for capital.

The $\varepsilon_{TC,Y}$ estimate of 0.868 implies significantly increasing returns to scale, a result largely driven by a very small capital-output elasticity. Scale expansions instead seem agricultural materials-using, although this conclusion is closely linked to the inclusion of t in the λ_K and λ_{MA} specifications. When *t* is not included as an argument in these specifications, output increases instead appear M_A-saving ($\varepsilon_{MA,Y}$ is significantly smaller than 1), and the $\varepsilon_{K,Y}$ and $\varepsilon_{TC,Y}$ estimates are much closer to 1, more closely approximating constant returns to scale overall.

Table 2 reports elasticity and contribution measures for two periods— 1972–82 and 1982–92. Note that the share of agricultural materials in total costs fell noticeably over time, from 0.273 to 0.226. The declining elasticity, combined with factor price inflation of less than 1% per year, meant that agricultural materials had virtually no contribution to the observed total cost increases of 4.17% per year in food processing in 1982–92. By contrast, the growing cost share of capital, along with factor price increases, led to a continued impact on increased processing costs. Moreover, the scale elasticity changed little between the 1970s and 1980s; continued modest demand growth therefore led to dampened effects on total costs.

Patterns of Agricultural Materials Demand

The drivers of agricultural materials (M_A) demand may also be examined using the measures reported in table 3, as specified in equation (4). The own price elasticity, $\varepsilon_{MA,pMA} = -1.138$, implies that M_A demand is fairly elastic. Own price increases (holding other factors constant) lead to disproportionately lower M_A demand. Based on observed p_{MA} trends, own prices thus provided a negative contribution of $C_{MA,pMA} = -0.062$ (6.2% per year) to the overall observed increase in M_A use of 0.038 (or 3.8% per year); other factors outweighed the negative own-demand effect.[15]

Table 3. The Demand for Agricultural Materials

	$\ln\Delta$	$\varepsilon_{MA,i}$	$C_{MA,i}$
Input prices			
Agricultural materials	0.0547	−1.1375*	−0.0622
Food materials	0.0403	0.0868	0.0035
Other materials	0.0653	0.2399*	0.0157
Labor	0.0908	0.1306	0.0119
Capital	0.0680	0.6490*	0.0441
Energy	0.1186	0.0312*	0.0037
Output	0.0218	1.0946*	0.0238
Technical change			
Equipment and structures	0.0200	0.7159	0.0143
t		−0.0390*	−0.0078
*t*2		−0.4248*	−0.0207
Sum			0.0439

Note: See table 1.

[15] These contributions were computed by multiplying the averaged elasticity and price change measures, rather than averaging the multiplied measures. Although most measure differ little across these two possible methods, the $C_{MA,pMA}$ and $C_{MA,Y}$ contributions do appear larger this way than they do when the contributions are first computed and then averaged (−0.62 as compared to −0.44 for the former, and 0.24 versus −0.17 for the latter).

Table 4. Temporal Decomposition of the Demand for Agricultural Materials

	lnΔ	$\varepsilon_{MA,i}$	$C_{MA,i}$	lnΔ	$\varepsilon_{MA,i}$	$C_{MA,i}$
	1972–82			1982–92		
Input prices						
Agricultural materials	0.1021	–0.9731*	–0.0994	0.0080	–1.2992*	–0.0104
Food materials	0.0687	0.0791	0.0054	0.0123	0.0943	0.0012
Other materials	0.1048	0.2094*	0.0219	0.0264	0.2699*	0.0071
Labor	0.1334	0.1082	0.0144	0.0489	0.1527	0.0075
Capital	0.1076	0.5484*	0.0590	0.0291	0.7479*	0.0217
Energy	0.2410	0.0281*	0.0068	–0.0019	0.0343*	–0.0001
Output	0.0266	1.0452*	0.0278	0.0170	1.1433*	0.0194
Technical change						
Equipment and structures	0.0244	0.7008	0.0171	0.0156	0.7307	0.0114
t		–0.1174*	–0.0235		0.0381*	0.0076
*t*2		–0.0608*	–0.0060		–0.7828*	0.0000
Sum			0.0302			0.0573

Note: See table 1.

All other inputs are substitutable with M_A, as is apparent from their positive price elasticities, and the observed increases in these input prices over the sample period thus imply positive shift effects on M_A demand that in sum more than compensate for the own price effect. In particular, M_A seems somewhat substitutable with both M_F and M_O, but the contributions of p_{MF} and p_{MO} changes (0.0035 and 0.016, respectively) are not substantial since the price changes have been small. Labor and energy prices rose more, but their contributions to M_A use (0.012 and 0.004, respectively) were limited by smaller substitution elasticities.

The contribution of increased capital prices to agricultural materials demand is much greater than the price effects associated with other inputs ($C_{MA,pK} = 0.044$). If weighted by p^*_K, which rose more rapidly than p_K, the contribution is even greater, at 0.056. Output growth also had a more than proportional effect on M_A demand; the elasticity of 1.095, evaluated at observed demand growth levels, implies an output demand contribution ($C_{MA,Y}$) of 0.024.[16]

Table 4 reports a temporal decomposition of agricultural demand, similarly to that in table 2 for costs. Note that the own price elasticity of demand for agricultural materials became considerably greater as time passed—from –0.97 in 1972–82 to –1.30 in 1982–92 (which, with a standard error of 0.05, is a statistically significant difference). In turn, all cross-price elasticities increased in the later from the former period, and the pattern suggests technical change that allows for easier substitution among inputs. The measures in table 4 also show that output expansion became more intensive in the use of agricultural materials in the 1980s, as the $\varepsilon_{MA,Y}$ elasticity increased to 1.143 from 1.045. But as output growth slowed, the contribution of output growth to agricultural demand growth also slowed.

[16] The test of significance for this measure compares to one rather than zero.

Technical Change and Agricultural Materials Use

Our model allows for three sources of technical change. It directly captures effects embodied in new investment in equipment and structures through ES. Equations (2) for total cost, and (5) for agricultural materials demand, capture the other sources. That is, the direct effects of disembodied technical change are reflected by a time trend that shifts the cost function. And technical change operating through effective prices for labor and capital is accommodated by allowing the gaps between the effective and observed prices to vary over time. In addition, the shift terms and decompositions represent time differences in the impacts of technical change.

First, our inclusion of ES as a cost-determinant in addition to the standard time trend *t*, to capture technical change embedded in new equipment and structures, seemed important in preliminary empirical investigation for explaining cost- and input-demand patterns. The ES parameters, interpreted as the impact of technical change embodied in

Table 5. Disembodied Technical Change: Direct and Indirect Effects

	$C_{\mathrm{MA},t(\mathrm{tot})} =$	$C_{\mathrm{MA},t(\mathrm{dir})} +$	$C_{\mathrm{MA,p^*MA},t} +$	$C_{\mathrm{MA,p^*K},t}$
Agricultural materials				
Full sample, t	−0.0078*	−0.0525*	0.0284*	0.0166*
1972–82, t	−0.0235*	−0.0632*	0.0222*	0.0174*
1982–92, t	0.0076*	−0.0420*	0.0353*	0.0147*
Full sample, $t2$	−0.0207*	−0.0126*	−0.0041*	−0.0039*
1972–82, $t2$	−0.0006*	−0.0126*	−0.0054*	−0.0060*
Total cost				
Full sample, t	0.0004*	−0.0042*	−0.0062*	0.0108*
1972–82, t	−0.0071*	−0.0126*	−0.0062*	0.0118*
1982–92, t	0.0078*	0.0041*	−0.0061*	0.0092*
Full sample, $t2$	−0.0141*	−0.0123*	0.0009*	−0.0025*
1972–82, $t2$	−0.0052*	−0.0026*	0.0011*	−0.0036*

Note: The total contribution ($C_{\mathrm{MA},t(\mathrm{tot})}$) is the sum of the three direct and indirect terms. Asterisks denote 95% statistical significance.

the capital stock, tended to be significant and plausible. When $t2$ was also included to represent the potential impact of structural changes in the 1980s, the $t2$ parameters became statistically significant but the ES parameters lost significance. The ES parameters remained jointly statistically significant, however, so they were retained in the final specification. Both variables thus seem to reflect changes in the 1980s—perhaps toward greater capital- or high-tech-intensity of production. And escalation of the ES ratio seems to have had a positive (but statistically insignificant) impact on agricultural materials demand; $C_{\mathrm{MA,ES}} = 0.011$.

Second, we may consider the direct and indirect effects of disembodied technical change on M_{A} demand, as summarized in table 5. The overall impact is represented by the contribution $C_{\mathrm{MA},t(\mathrm{tot})}$, which is -0.008 on average. The trend in this contribution is also substantively and statistically relevant; the $\varepsilon_{\mathrm{MA,t}}$ (tot) estimates are significantly different from zero for most individual observations, and the trend was augmented post-1980 ($C_{\mathrm{MA},t2(\mathrm{tot})} = -0.021$). Aggregated over time, the estimates suggest a 17% decline in agricultural demand, holding food demand constant, over the full period.

The direct impacts exhibit a much greater magnitude than the total or overall measures, however, since large proportions of the direct effects are counteracted by effective price trends that may be interpreted as embodied technical change or adjustment costs. These patterns can be seen from the decompositions of direct and indirect impacts in table 5, that arise from the inclusion of t-terms in the p^*_{MA} and p^*_{K} (λ_{MA} and λ_{K}) specifications, as in equation (5).

In particular, the direct effect, $C_{\mathrm{MA},t(\mathrm{dir})}$, captures the temporal shift in the M_{A} demand curve, holding output and factor prices fixed. This effect is quite large; agricultural demand not accounted for by other factors falls by 5.25% per year, with a greater decrease in the 1972–82 than the 1982–92 period. The direct disembodied effects on costs are much more modest -0.42% per year—with a larger rate of decline in the 1970s. This is very consistent with most other studies of food-processing productivity, including Heien; Gopinath, Roe, and Shane; and Morrison; as well as with more general studies of productivity patterns across industries, such as Jorgenson and Stiroh.

These large direct effects are offset by two indirect effects, operating through changes in effective agricultural materials and capital prices. The effective price p^*_{MA} rose by only 3.6% per year as compared to the p_{MA} growth of 5.5% per year. This lower growth in p^*_{MA} could derive from various factors—including augmented quality that is not captured in the measured values—but is inconsistent with increases in market (monopsony) power.[17] Thus, it appears that λ_{MA} may reflect technical change or productivity embodied in agricultural materials, representing the impact of technical innovation in agricultural markets transferred to the next level of the food chain–food processing.[18]

[17] Monopsony power is not evident overall for these markets, unless it is counteracted by quality changes, because it is generally (and on average) the case that $p^*_{\mathrm{MA}} < p_{\mathrm{MA}}$ rather than the reverse.

[18] From the point of view of processors, quality changes could include shifts toward more consistent and uniform livestock shapes that allow for lower cost processing, or from development of crop varieties better suited to modern processing practices. Quality changes could also stem from developments occurring between the farm gate and the processing plant, such as improvements in

By contrast, effective capital prices grew faster than their measured values. Factors driving this trend could include substantive and rising adjustment costs (perhaps from larger scale and more high-tech production resulting in greater production rigidities), environmental or safety standards, or taxes, that are not effectively captured in the measured user cost of capital. These trends in capital costs motivate a substitution effect toward primary agricultural products.

Because the full trend impact on agricultural materials demand is the sum of terms involving the direct- and indirect-t-effects exhibited through the trend in p_k^*, and the trend component of p_{MA}^* is negative ($\varepsilon_{p^*\mathrm{MA},t} = -0.125$), for our scenario $\varepsilon_{\mathrm{MA,pMA}} < 0$. However, the indirect p_{MA}^* effect on M_{A} use is positive—as is the p_{K}^* effect because K is a substitute but p_{K}^* is rising ($\varepsilon_{p^*\mathrm{K},t} = 0.128$). Thus each of these components partially counteracts the large direct t-impact of –0.0525. This evidence is consistent with the embodied technical change interpretation of the t-impacts on effective prices implied by our comparison of p_{MA}^* and p_{K}^* to p_{MA} and p_{K} changes. Declines in effective relative to measured p_{MA}, and the reverse for p_{K}, each augment M_{A} use.

Note also that the input-specific measure $C_{\mathrm{MA},t(\mathrm{dir})} = -0.0525$ is much larger than the associated *overall* (total cost) input declines captured by $C_{\mathrm{TC},t(\mathrm{dir})} = -0.004$. And that the total M_{A} effect, $C_{\mathrm{MA,t}}(\mathrm{tot})$, is negative whereas that for TC, $C_{\mathrm{TC,t}}(\mathrm{tot})$, is positive, indicating that "technical change" has been both relatively and absolutely M_{A}-input-saving. Over time there has been a technical change bias toward reducing agricultural materials use more than other inputs for a given level of output.

Finally, the effective price p_{MA}^* actually trends down after 1980, so the full contribution of own price changes to agricultural demand is positive—a tendency that is particularly worth highlighting because measured agricultural prices continued to fall after our sample period. It also appears that although agricultural demand growth in the 1980s exceeded that in the 1970s, the individual input-price contributions of output and input prices to that growth were generally smaller. In fact, a large proportion of agricultural demand expansion seems to have arisen from technical effects. In particular, the indirect p_{MA}^* effect has increased over time to the point where $C_{\mathrm{MA},t(\mathrm{tot})}$ is positive post-1980, although the direct impact, $C_{\mathrm{MA},t(\mathrm{dir})}$, reported in table 2, remains negative (but smaller) in the later time period.

Effects of Agricultural Price Changes on Marginal Costs, Average Costs, and Food Prices

We may also consider the pass-through of agricultural prices, using the estimates presented in table 6 for the elasticity and contribution measures relating to marginal cost and food prices. Input-price effects for materials and labor inputs are slightly larger for marginal than for total (and thus average, given Y) cost, implying a depressing impact on scale economies (MC increases more than AC with higher input prices, so their ratio rises). The reverse is true, however, for the p_{K} and p_{E} elasticities, supporting the notion that capital is subject to adjustment costs and "lumpiness" that are driving forces for returns to scale. This observation is also consistent with the virtually nonexistent MC impacts of changing output.

Table 7 reports elasticities for food prices, marginal processor costs, and total (average) processor costs for a 1% change in agricultural prices. First, comparisons of food prices and marginal costs provide insights about markups and their determinants. A 1% increase in agricultural prices increases food prices by proportionately more than average costs, and marginal more than average costs—0.272, compared to 0.253, and 0.250, respectively. In turn, rising agricultural prices drive slightly higher markups (p_{Y}/MC). The elasticity measures also changed substantively over time. In particular, the food price elasticity fell sharply, from 0.308 in 1972–82 to 0.237 in the later period, and moved closer to the cost elasticities.

Conclusions

Our analysis investigates an often-raised and widely discussed trend that has generated significant concern about agricultural markets. Steady changes toward more highly processed food products have been observed for many years, and the connections among those trends and fundamental changes in household demographics and lifestyle choices have been extensively documented. It is easy to see the key implications of such developments for agriculture; descriptive data alone would show

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transportation, storage, cleaning, and sorting that narrow the gap between the plant level cost of an input and the farm gate price. The PPIs that provide the basis for our market price measures are measured at the farm, not the plant.

Table 6. Marginal Cost and Price Elasticities and Contributions

	$\ln\Delta$	$\varepsilon_{\mathrm{MC},i}$	$C_{\mathrm{MC},i}$	$\varepsilon_{\mathrm{PY},i}$	$C_{\mathrm{PY},i}$
Input prices					
Agricultural materials	0.0547	0.2533	0.0139	0.2725	0.0149
Food materials	0.0403	0.2080	0.0084	0.2131	0.0086
Other materials	0.0653	0.1938	0.0127	0.2078	0.0136
Labor	0.0908	0.1611	0.0146	0.1732	0.0157
Capital	0.0680	0.1773	0.0121	0.1887	0.0128
Energy	0.1186	0.0065	0.0008	0.0086	0.0010
Output	0.0218	−0.0157	−0.0003	−.0776	−0.0017
Technical change					
Equipment and structures	0.0200	0.0328	0.0007	0.0340	0.0007
t	0.0100	−0.0139	−0.0028	−0.0149	−0.0030
$t2$		−0.0042	−0.0002	−0.0042	−0.0002
Sum			0.0634		0.0654

Note: See table 1. Here, each contribution (C) is the product of the growth rate in the first column and the relevant elasticity.

Table 7. Impacts of a 1% Agricultural Price Increase on Food Processing

	Full Sample	1972–82	1982–92
	Percentage change		
Total cost	0.250*	0.273*	0.226*
Marginal cost	0.253*	0.287*	0.220*
Output price	0.272*	0.308*	0.237*
Ag input quantity	−1.137*	−0.973*	−1.299*

Note: See table 1.

that the share of agricultural materials inputs in food-processing shipments fell over time, in amounts close to the values presented in table 2. By inference, the linkage between agricultural and food prices should also have weakened in accordance with the trend change in factor shares.

A more detailed analysis of these patterns can be developed, however, by characterizing a more complete model of the network of factors driving demand for agricultural commodities in food processing. In this study, such an approach has yielded insights about several less widely understood—particularly quantitatively—factors affecting the demand for agricultural products.

First, in line with earlier findings by Goodwin and Brester, we find that processors' demand for agricultural commodities is price sensitive, and has become more elastic over time. Along with falling relative prices for agricultural inputs, this has led to substitution toward agricultural inputs, and away from labor and capital. Second, we find that the demand for agricultural materials is slightly scale intensive; increases in industry demand for food products lead to more than proportionate increases in agricultural input demand. Thus, modest continuing food industry growth has led to a slight intensification of agricultural demand growth. And third, we find that some forms of technical change have intensified agricultural input demand. Effective agricultural prices have dropped relative to observed prices, a trend that is likely driven by quality improvements in agricultural commodities and in the marketing system, and in our model leads to more substitution toward agricultural materials. Moreover, effective capital prices have risen relative to observed, possibly due to growing adjustment costs, or tax, regulatory, or environmental wedges, which reinforces substitution toward agricultural inputs.

Conversely, the direct impact of technical change (t) has been large and negative, and only partly counteracted by the positive technological impacts embodied in the effective M_{A} and K prices. The implied drop in primary agricultural product demand has also been stronger than the overall cost diminution effect, which implies a relative M_{A}-input-saving bias. The 1982–92 ($t2$) structural change impact also suggests that this trend is intensifying, and is being further exacerbated by diminishing effective price (p^*_{MA} and p^*_{K}) changes.

In sum, the effect of changes in consumer preferences on agricultural input demand appears to have been much greater than descriptive statistics suggest, since the descriptive measures co-mingle all of the above forces. Overall, the measured share of primary agricultural materials in total costs has been dropping, so the contribution of M_A price increases to cost changes has fallen over time. As a result, the link between M_A demand and food prices has clearly weakened, and this trend is likely to continue into the future.

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Appendix

Table A.1. Parameter Estimates from GL-Q Model

Parameter	Estimate	*t*-statistic	Parameter	Estimate	*t*-statistic
λ_{MA1}	0.0951	1.53	δ_{MAT}	−0.1887	−2.54
λ_{MA2}	0.0712	1.56	δ_{MAT2}	0.4743	2.62
λ_{MAt}	−0.0906	−5.31	δ_{MAES}	0.1488	0.66
λ_{K1}	−0.1089	−1.24	α_{L}	0.1524	0.62
λ_{K2}	−0.2256	−3.74	δ_{LY}	0.0822	11.24
λ_{Kt}	0.1536	4.79	α_{LMF}	−0.1789	−2.11
α_{E}	−0.0522	−1.11	α_{LMO}	0.4867	2.72
δ_{EY}	0.0147	2.23	δ_{LK}	−0.1017	−0.53
α_{LE}	−0.0228	−0.82	δ_{LT}	−0.1230	−4.63
α_{EMA}	0.0226	1.86	δ_{LT2}	0.3691	4.59
α_{EMF}	−0.0002	−0.02	δ_{LES}	−0.1718	−1.89
α_{EMO}	−0.0581	−1.19	α_{MF}	−0.6892	−2.29
δ_{EK}	0.1208	2.35	δ_{MFD}	0.1298	0.72
δ_{ET}	−0.0791	−4.80	δ_{MFY}	0.0889	9.85

(Continued)

Table A.1. *(Continued)*

Parameter	Estimate	*t*-statistic	Parameter	Estimate	*t*-statistic
δ_{ET2}	0.4020	6.39	α_{MFMO}	−0.0537	−0.44
δ_{EES}	0.0294	0.70	δ_{MFK}	0.2563	1.93
γ_{YT}	−0.0006	−3.87	δ_{MFT}	−0.0896	−2.42
γ_{YT2}	0.0001	0.33	δ_{MFT2}	0.4720	4.85
γ_{YES}	0.0018	1.21	δ_{MFES}	−0.1769	−1.30
γ_{TES}	−0.0028	−0.96	α_{MO}	−0.4973	−1.17
γ_{T2ES}	0.0018	−0.24	δ_{MOY}	0.0471	5.90
γ_{TT2}	−0.0748	−6.59	δ_{MOK}	0.0249	0.06
γ_{YY}	−0.0002	−1.37	δ_{MOT}	−0.1108	−2.95
γ_{TT}	0.0305	7.32	δ_{MOT2}	0.4105	4.12
γ_{ESES}	0.0118	0.84	δ_{MOES}	−0.4599	−3.88
α_{MA}	0.5887	1.12	α_{K}	−1.4212	−2.64
δ_{MAY}	0.7710	56.13	δ_{KY}	0.1643	19.01
α_{LMA}	0.0824	0.98	δ_{KT}	−0.0373	−0.86
α_{MAMF}	0.0574	0.39	δ_{KT2}	0.4104	3.45
α_{MAMO}	0.0137	0.11	δ_{KES}	0.3393	2.56
δ_{MAK}	0.3775	2.84	λ_{Y}	−0.0008	−0.54

Table A.2. R^2 Coefficients from GL-Q Model

Equation	R^2
TC	0.976
M_A	0.993
M_F	0.946
M_O	0.954
L	0.946
E	0.948
K	0.979
P_Y	0.976